How the News Media Activate Public Expression and Influence National Agendas

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1Based on joint work with Benjamin Schneer and Ariel White (Science 2017)
2GaryKing.org
Introduction

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Statistical Problems: We Can’t Randomize

• Statistical Problems
• Randomization: usually impossible
• Endogeneity: media outlets compete for readers
• Spillover: 1 intervention may affect all potential subjects

• Clever Research Designs (trying to approximate randomization)
  • New TV tower. Some behind hill, in radio shadow
  • Before/after studies of “surprise” media events
  • Roll out of Fox News to some towns and not others
  • Many others…

• But we still can’t randomize
• Assumptions: better, but unavoidably dubious
  ⇝ “Profound biases,” > 600% difference from truth
• Estimands: different, of sometimes questionable relevance
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Political Problems: They Won’t Let Us Randomize

What we’d do without constraints
- Sign up many news media outlets
- Randomize news content and timing for each
- Control collaboration to induce cross-outlet correlations

Why is this plan so hard for media outlets?
- Need to take actions few (if any) have ever before agreed to
- Outlets are competitors: trying to scoop each other
- Must share information with us (even if not with each other)
- Need numerous agreements, technical infrastructure for large scale collaboration & data collection, extensive coordination, high levels of trust

More specifically, to randomize
- Journalists require: total control over what’s published & when
- Scientists require: total control over what’s published & when
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Our Approach:

Let's Randomize

• Build trust: 5 years of negotiating & communicating
• Develop incentive compatible research design: both get 100%, no compromises; ⇝ solve a political problem technologically
• Convince 48 media outlets to let us experiment on them
• Whenever possible, choose realism (even if inconvenient)
• Stick close to outlets’ standard operating procedures
• Embed treatment within ordinary routines
  • More expensive, logistically complicated, and time-consuming, but more generalizable
• Goal: Build platform to continue experiments
• A work of: political science
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Define Outcome Variable: Types of News Media Effects

- **Individual-level Effects**
  - Outcome variable: individual knowledge and opinion
  - Effects: Persuasion, attitude formation, diffusion, gatekeeping, priming, issue framing, etc.
  - Measurement: survey research

- **Collective Effects: Impact on the national conversation**
  - Outcome variable: activated public opinion, views of all those trying to express themselves publicly about policy and politics
  - Classic definition of public opinion, predating survey research
  - Measurement:
    - Previously: hallway conversations, "water-cooler events", soapbox speeches in public squares, editorials, etc.
    - Now: 750M public social media posts/day
  - Target population: different than survey research!
    - Surveys: pop quizzes of everyone, even uninformed & inactive
    - Social media: counts only activated opinion
  - Democracies: Can ignore individuals, but collective expression sets agendas
  - Autocracies: Ignore criticism, but censor expression about collective action
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- Signup 48 small media outlets (& > 12 others just for info)
- 17 for trial runs, 33 in experiment, 2 in both
- Median size: The Progressive, 50,000 subscribers

Examples:
- Establish 11 broad policy areas
- Rules: (a) major national importance; (b) interest to outlets
- race, immigration, jobs, abortion, climate, food policy, water, education policy, refugees, domestic energy production, and reproductive rights
- Using 11 rather than 1: more representative; larger \( n \) needed
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Research Design
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![Magazine Covers]

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Examples:

- Establish 11 broad *policy areas*
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  ![Magazines]

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  • race, immigration, jobs, abortion, climate, food policy, water, education policy, refugees, domestic energy production, and reproductive rights
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  ![Magazines](image.png)

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    - Using 11 rather than 1: more representative; larger *n* needed
Treatment

• We choose a policy area

• Outlets volunteer for a pack of 2–5 (with our approval), following “project manager” protocol (e.g., Panama Papers)

• The pack chooses subject for articles

• We approve: If rejected outlets can publish outside experiment

• Requirement: No breaking news (stories may be held for weeks)

• Options: large investigations, interview-based journalism, opinion pieces, or others normally published by pack members

• Example. Policy area: technology policy. Subject: what Uber drivers think about driverless cars, or how a trade agreement affects hiring in Philadelphia

• Outlets Publish Simultaneously: (following usual procedures)

• One article on subject per pack member

• Distribute via website, print, video, podcast, etc.

• Promote via Google adwords, social media, email lists, SEO…

• Co- and cross-promote with outlets in same pack
Treatment

- We choose a policy area (1 of 11)
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Matched Pair Randomization

• Select pair of weeks: matched on similarity of predicted news
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• Treatment week: publish & promote articles (usually Tuesday)
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(Ex post: Predictions accurate; flips, news shocks uncorrelated)
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**SEPTMBER 2015**

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Research Design
Randomization

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![Calendar](calendar.png)

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*Treatment Week*

*Control Week*
Randomization

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![September 2015 Calendar](calendar-image)
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#### Reasoning

- Cf. complete randomization: more power, efficiency, & "political" robustness; less bias, model dependence, & research costs; SEs as much as 600% smaller (Imai, King, Nall 2008)
- Few experiments/outlet: Less interference; more heterogeneity
- Nation as unit of treatment: no spillover, more cost
- **(Ex post:** Automated text analysis & qualitative evidence: indistinguishable from normal publications & practices; no outlet received a single complaint)
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Random Treatment → Articles Published → Pageviews → Posts on Subject → Posts in Policy Area

Intervention • Downloads from outlets • Special access to Google Analytics • Social media: King, Pan, Roberts (2017) • Social media: Crimson Hexagon, Inc.; Methods: readme, 2010; readme2, 2018
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Research Design
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Determining $n$ via Sequential Hypothesis Testing

Most analysts: fix $n$, run experiment, discover $p$-value

If $n$ is too large: waste time & resources
If $n$ is too small: waste the entire experiment
$\Rightarrow$ neither is acceptable with such massive logistical costs

Power calculations: require knowing QOI!

Better: fix $p$-value, run experiment sequentially, discover $n$

Collect only as much data as you need (Why should you be in grad school longer than necessary?)

Valid statistically under likelihood or Bayes (Careful of misinformation in some applied literatures)

Need to check sensitivity to priors and models

We introduce new methods to:

- Evaluate robustness under frequentist theory
- Remove parametric assumptions
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Research Design

Results

Supporting Analyses

Implications
Results from Sequential Hypothesis Tests

Our Stopping Rule:

- $p \leq 0.05$
- joint test: day 1, 2, 3, policy, subject;
- for $n$, $n-1$, & $n-2$

Recognizing more data is better and logistics are complicated (they might stop us!)

Empirical result:

- $n = 70$ (35 experiments)

Frequentist validation:

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\[\begin{array}{cccccc}
\text{Agree} & \alpha = 0.05 & 0.0 & 0.1 & 0.2 & 0.3 & 0.4 & 0.5 \\
\text{Joint} & 1 & 1-2 & 1-3 & 1-4 & 1-5 & 1-6 \\
\text{Subject} & 0 & 0 & 0 & 0 & 0 & 0 \\
\text{Policy} & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{array}\]

• **Frequentist validation:** extensive [non]parametric tests
Main Causal Effect: Public Expression in Policy Areas

<table>
<thead>
<tr>
<th></th>
<th>0</th>
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<td>●</td>
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<td>Day 2</td>
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<td>Day 4</td>
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<td>Day 5</td>
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<td>Day 6</td>
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- **Open circles:** model-free estimate (no model, higher variance)

**Causal effects:**
- 1st day: 19.4% increase,
- Total: 62.7% increase

**Context:**
- 3 small media outlets have huge effect on the national conversation
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- **Red Dots:** Original (model-based) estimates
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Results: no dominant outlet; high heterogeneity
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Jackknife Estimation on Policy Area Effects

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High Experimental Compliance

• # Articles published by pack in policy area

What's the goal?

• Average # media outlets per pack:

3.1

Causal effect on # articles:

2.94

⟹ high compliance

Pageviews (on subject of articles, relative to a day's volume)

• Causal effect on # pageviews:

969.6% (52,223 views) increase

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- More Results
  - Opinion change: 2.3% change in direction of article opinion
- Large news media outlets: Observational evidence, >15x effect
- Robustness checks
  - # of unique authors: little change from effect on posts
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 Small outlets: very large average effects on pageviews, agenda (subject & policy), opinion change

 Larger outlets: even bigger average effects

 Heterogeneous effects: large, highly variable viral patterns

 Implications: for individual journalists

 Remarkable power; serious responsibility; not just another job

 Implications: for ecosystem of media outlets

 Control over editorial boards and mastheads

 Balance and diversity of outlet opinion

 Effects of fake news

 Impact on agendas, elections, public policy, discourse

 Journalism jobs: 25% drop in last decade

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 We wrote a paper, built a platform, & showed how others can

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For more information:
GaryKing.org/media
Notation and Quantities of Interest

- **Outcome Variable:** $y_{ped}$, number of social media posts in policy area $p$ ($p = 1, \ldots , 11$)
- **Experiment:** $e$ ($e = 1, \ldots , E$)
- **Day of and after intervention:** $d$ ($d = 1, \ldots , 6$)

- **Treatment Variable:** $T_{ped}$, instruction to pack (of 2-5 outlets) to write, publish, and promote articles, like a project manager
- **Treated weeks:** $T_{ped1} = \ldots = T_{ped6} = 1$
- **Control weeks:** $T_{ped1} = \ldots = T_{ped6} = 0$

- **Quantities of Interest**
  - **Absolute Increase:** $\lambda_d = \text{mean}_{p,e}[Y_{ped}(1)] - \text{mean}_{p,e}[Y_{ped}(0)]$
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Model-Based Approach

• Transform outcome variable for normality & homoskedasticity:
  \[ z_{ped} = \ln(y_{ped} + 0.5) \]

• The Model:
  \[ E(z_{ped} | T_{ped}) = \beta_0 + \beta_p + \eta_d + \gamma_d T_{ped} \]
  - \( \beta_0 \): constant term
  - \( \beta_p \): fixed effects for the 11 policy areas
  - Assume linearity over days:
    \[ \eta_d = \eta_0 + \eta_1 d \]
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  - Assume conditional independence over \( p, e, d \)

Model-Free Approach:

• Drop linearity & conditional independence assumptions
• Regress \( z_{ped} \) on \( T_{ped} \) separately for each \( d \)
  - Equivalent to difference in means for each day
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